Journal of Soft Computing in Civil Engineering 8-2 (2024) 102-118

Contents lists available at **SCCE**

Journal of Soft Computing in Civil Engineering

Journal homepage: www.jsoftcivil.com

Ground Vibrations Prediction Using Artificial Neural Networks

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https://doi.org/10.22115/SCCE.2023.391609.1627

ARTICLE INFO

Article history:
Received: 02 April 2023
Revised: 04 August 2023
Accepted: 31 December 2023

Keywords:
Artificial neural network;
Soil dynamics;
Vibrations propagations;
Heterogeneous soil;
Time history responses.

ABSTRACT

Predicting the propagation of ground vibration wave, induced by highways, railways, electrical power plants and other industrial activities, in their vicinity is of paramount importance to evaluate the degree of nuisance to populations, buildings and sensitive equipment. The present study proposes a generalized artificial neural network (ANN) model able to predict the ground vibrations, at any distance in any type of soil, due to any source of vibration. The ANN network inputs are the distance between the measurement point and the excitation source, the soil characteristics for homogeneous soil or their equivalent characteristics for heterogeneous soil, as well as the amplitudes of the source acceleration time history. Its outputs are the acceleration time history responses of the free field points located at given distances from the excitation source. A large dataset including realistic and unrealistic soil properties is artificially generated in order to train and test the ANN. The database covers the characteristics of homogeneous and heterogeneous soils having homogenized properties. The time delay between the source and the distant point is accounted for using the cross-correlation product technique. The test results show that the correlation between the target ground acceleration signals and those predicted by the trained ANN model reaches 98%. Furthermore, the predictions of ground acceleration peaks have good accuracy, i.e. less than 2% error. Considering the unlimited possibilities to sample the soil properties combined to the homogenization and the synchronization techniques, the ANN model can be generalized to many practical applications.

How to cite this article: Derbal I, Bourahla N, Mebarki A, Bahar R. Ground vibrations prediction using artificial neural networks. J Soft Comput Civ Eng 2024;8(2):102–118. https://doi.org/10.22115/scce.2023.391609.1627

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1. Introduction

The propagation of vibrations in the ground from different sources is a common concern in urban, commercial or industrial areas. The construction of new buildings in close proximity to vibration sources such as trams, railways and highways increases the risk of important vibrations. Some sources give rise to stress waves that propagate in the ground and end up reaching the foundations of civil engineering structures by making them vibrate violently as it is the case during earthquakes. Other vibrations of technological origin such as those due to traffic (road or rail), thermal power stations, and machinery can also induce waves that propagate through the ground and cause nuisance or damage to adjacent buildings. It is therefore important to develop effective methods to reduce ground vibrations, especially when these vibrations are problematic. Vibration reduction can be evaluated numerically to avoid costly and time-consuming mockups and experiments. In order to develop such measurements, it is necessary to use numerical models capable of predicting the phenomena of vibration that occur in built environments.

In the literature there are several analytical, experimental and numerical methods that treat the ground motion and the propagation of vibrations in the soil [1–17].

Approaches, such as empirical methods are limited to peak responses (acceleration, velocity or displacement) prediction and do not give access to time history responses. Similarly, numerical calculation errors accumulate due to numerical dispersion and stray wave reflections.

Given the availability of data on the complex phenomena of the vibrations propagation in diverse heterogeneous soils, characterized by a high variability of geotechnical properties, makes the recourse to neural network (NN) models to predict ground acceleration at the near and far field of a vibration-emitting source an attractive alternative.

Several artificial neural networks models have been developed for the prediction of ground vibrations induced by blasting, railway traffic and earthquake motion.

Prashanth et al. [18] proposed an ANN model able to assess and predict the induced ground vibrations from blasting. The results show that the precision of the proposed model is remarkably high compared to seven other models, with a regression factor R approaching unity. At Masjed Soleyman earth dam in southwest of Iran, Abbaszadeh Shahri et al. [19] estimated and predicted blasting-induced ground vibration using two different ANN by developing the multilayer perceptron (MLP) and generalized feed forward neural network (GFNN), which showed very good performance. Nevertheless, the invisible random data used as validation process showed better performance and greater efficiency in the GFNN model compared to the MLP. In line with the research field of blast, Maryam et al. [20] presented IM–NN model based on itemset mining (IM) and neural networks (NN): 92 instances collected from blasting events of two surface mines in Iran, were used for the constitution of the database. They found that IM–NN has better performance than NN. Also, to predict the intensity of ground vibration induced by mine blasting operations, Bui et al. [21] propose an ANN based cuckoo search optimization (CSO), named as CSO–ANN model that showed the superior accuracy comparing with other stand-alone models

namely ANN, tree-based ensembles, support vector machine (SVM) and two empirical equations (Ambraseys and United States Bureau of Mines (USBM)). Recently, Yewuhalashet Fissha et al. [22] used Bayesian neural network and four machine learning techniques (gradient boosting, k-neighbors, decision tree, and random forest) to determine the peak particle velocity induced by the blast of the Mikurahana quarry, where the correlation reached 94%. Moreover, Runcai Bai et al. [23] rely on the deep neural network algorithm to study and analyze the optimization of blasting parameters and the prediction of vibration effects in open pit mines with high accuracy.

Other researchers have also used ANN to evaluate soil vibration induced by railway traffic. Paneiro et al. [24] predicted ground vibration amplitudes due to light railway traffic in urban areas applying ANN approach with quantitative and qualitative predictors. Among several trained and validated models, the best one was successfully obtained for Lisbon area with R^2= 0.9720. Similarly, a fast, high-accuracy prediction method has been proposed by Lei et al. [25], where an artificial neural network model has been trained using series of numerical samples generated by the finite element (FE) ANSYS software. The ANN predicted the level of vibration under certain conditions, with a maximum error less than 6.41% and an average error less than 2.29%. In the same field and by using deep learning precisely recurrent neural network and long short time memory RNN-LSTM model, Jakub Siłka et al. [26] managed to predict the vibrations generated by the trains with accuracy greater than 99%.

In another context, ANN models were also used to predict ground motion due to earthquakes. For example, Dhanya et al. [27] used ANN to predict a ground motion for shallow crustal earthquakes in terms of peak ground velocity, and 5% damped spectral acceleration. For the same purpose, Tabarsa et al. [28] predicted nonlinear dynamic responses of layered soils due to earthquake motion using ANN models. They have been trained and tested employing white noise signals. Under different earthquake excitations, the proposed model has achieved very precise prediction of the soil dynamic response. Furthermore, earthquake recordings have been exploited to train an ANN model to derive ground motion prediction model for the Himalayas and Indo-Gangetic plains [29]. For the prediction of the duration of strong ground motions, Flores-Mendoza et al. [30] proposed ANN models trained with a database of 3153 seismic records. The duration of strong ground motions predicted by ANN was in agreement with that calculated by the empirical equations except for some cases, where they exhibit abrupt changes.

In a previous study [31], a method based on artificial neural networks (ANN) has been developed to predict the time history ground responses at any point in the vicinity of a vibratory source. It was focusing on the particular case of vibrations generated by a reaction mass of a shaking table belonging to the Earthquake Engineering Research Centre in Algiers (CGS). The latter was to the case of only one type of soil, i.e. the soil surrounding the vibrating table of CGS. The purpose of the present paper is thus an extension which aims to cover any type of soil, even for heterogeneous soils. The database has been expanded to cover a wide variety of soil properties, within their realistic range of variations, and for any source signal (earthquake, artificial), i.e. not only shaking table signals. Coherence of the properties was not regarded as an essential issue as homogenization method is used to calculate the equivalent heterogeneous soil properties to serve as input to the ANN.

2. Principle and methodology

The ANN is conceived to have as input parameters: a vector of the acceleration time history of the source, a scalar equal to the distance between the source and a point in the surrounding soil (Fig. 1) and three scalars to account for the soil parameters (Young's modulus, Poisson's ratio and Density). The ANN outputs the acceleration response time history at that distant point from the source.

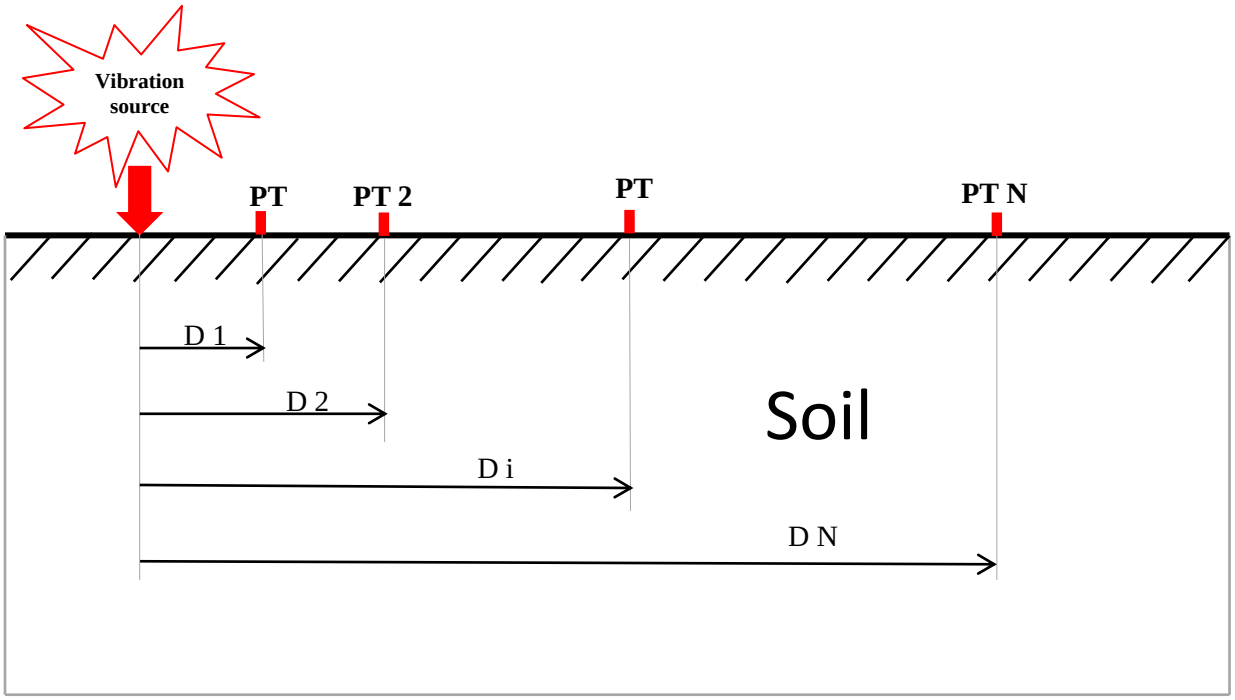

Fig. 1. Principle of the method.

The response time history at a point in the surrounding is characterized by a time delay with respect to the excitation signal at the source due to the wave propagation along the distance in the soil domain. Therefore, synchronization between the input and output signals is carried out before using them in the network.

The main contribution of this study is the constitution of an expanded database resulting from numerical models covering a very large spectrum of soil types. The idea is that the ANN predicts the response of an equivalent homogeneous soil properties obtained as a linear combination of real properties of the soil layers which necessarily belongs to the samples space composed of all possible combinations of the soil properties within their relative range of variation regardless whether the sample has realistic soil properties or not, as detailed in section 4.2.

3. Constitution of the database

In order to generate the database, a finite element numerical model of the soil and an excitation source is elaborated using the COMSOL Multiphysics software [32]. The excitation source is

materialized by a reinforced concrete cube (0.5×0.5×0.5m).The excitation block and the surrounding soil are represented by solid (volumetric) elements: 39 vertex elements, 106 edge elements, 5,927 tetrahedral elements and 1,102 triangular elements. The characteristics of the soil are explicitly introduced into the model, namely Young modulus E, Poisson ratio υ and Density ρ. The damping of the soil adopted is Rayleigh damping with a ratio ξ = 10% [33].

The mass is embedded in the soil on the sides and at its base; it is regarded as an infinite ground. The mesh of the model is of tetrahedron type as illustrated in the Fig. 2.

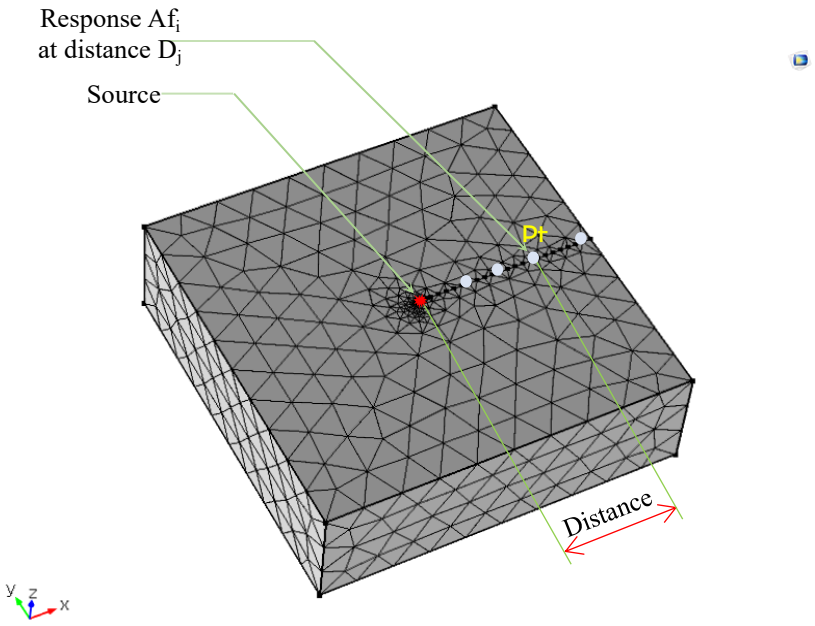

Fig. 2. ANN database principle.

A Parametric Sweep option available in the COMSOL software provides an opportunity to solve a set of problems obtained by varying some parameters of interest.

This feature has been used to vary the soil properties represented by Young's modulus, Poisson ratio and the density. The Parametric Sweep option generates automatically several models at the same time.

Acceleration ground motions (a random acceleration signal (white noise) to cover a wide frequency band) (A_i) are applied on the excitation block in order to generate vibrations at the source. The acceleration response signals (Af_i) are obtained at free field ground points (Pt_i) located at different distances (D_j) from the source. The ANN database is constituted of A_i (array), D_j (scalar), Young modulus (scalar), Poisson ratio (scalar) and Density (scalar) as inputs and Af_i (array) as the outputs of the ANN. [AM's comments: use either subscript "i" or "j" so that Pt_i should be denoted Pt_j in order to keep coherent subscripts with D_j for instance]

A time offset between the source signal and the recorded signal at a distance (D_j) from the source is observed because of a delay due to the propagation of vibration waves. This delay can be estimated using cross-correlation product [31].

Input and output acceleration signals will be synchronized with this method before operating them in the proposed network.

4. Neural Network Analysis

The proposed network is designed to predict the propagation of vibrations induced by any source of excitation in any type of soil.

4.1. Neural Network Design

According to the literature [31,34], a feed-forward back-propagation network with a single hidden layer can approach any continuous function with the desired accuracy [35]. For accurate prediction of ground acceleration signals, we used a backpropagation feedforward network as the most appropriate model to solve an identification problem.

The input of the network is composed of 15 parameters: a distance between the measurement point and the source D_j, Young's modulus, Poisson ratio, soil density and for each acceleration amplitude $A(t_i)$ of the source time history , five (5) amplitudes before $A(t_i\text{-}5)$, $A(t_i\text{-}4)$, $A(t_i\text{-}3)$, $A(t_i\text{-}2)$, $A(t_i\text{-}1)$ and five (5) amplitudes after $A(t_i+5)$, $A(t_i+4)$, $A(t_i+3)$, $A(t_i+2)$, $A(t_i+1)$ are added. The acceleration amplitude $Afj\ (t_i)$ of the response time history at a free field location at a distance D_j from the source excitation is used as the output of the network. (Fig. 3)

Soil parameters (Young's modulus, density and Poisson's ratio) have been introduced to the network in order to extend its use to different soil types unlike antecedent work [31].

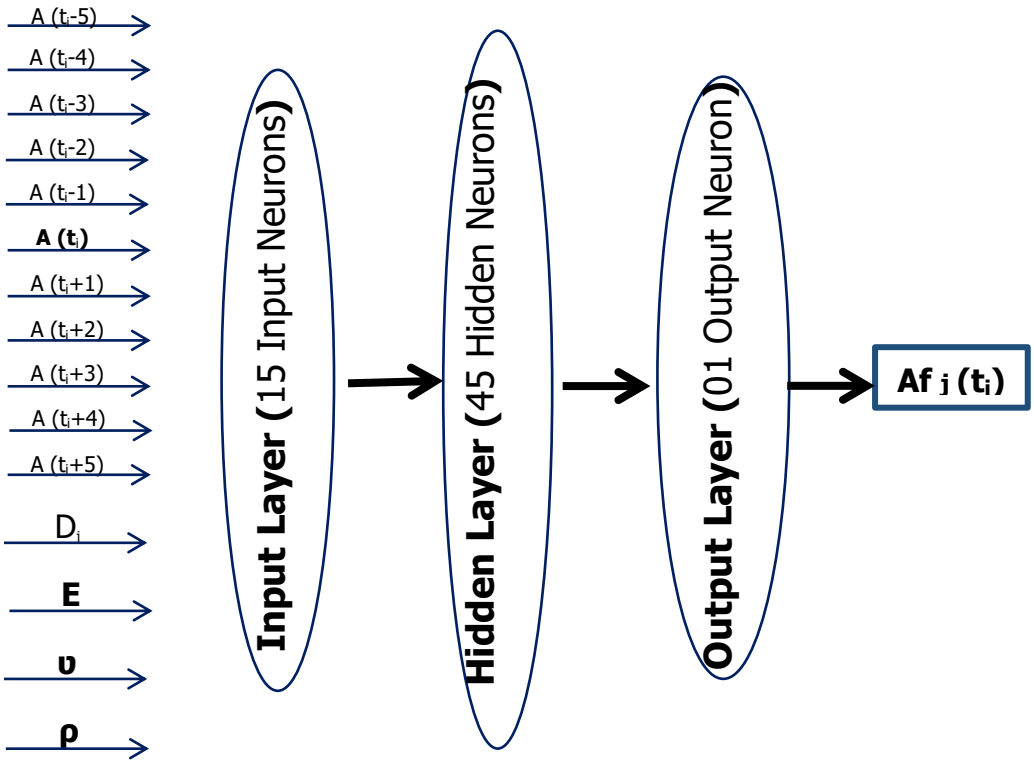

Fig. 3. Design of the ANN model.

The neurons of the hidden layer in this network have transfer functions of the tangential sigmoid type. The transfer function in the neurons of the output layer is of the linear type. (Fig. 4)

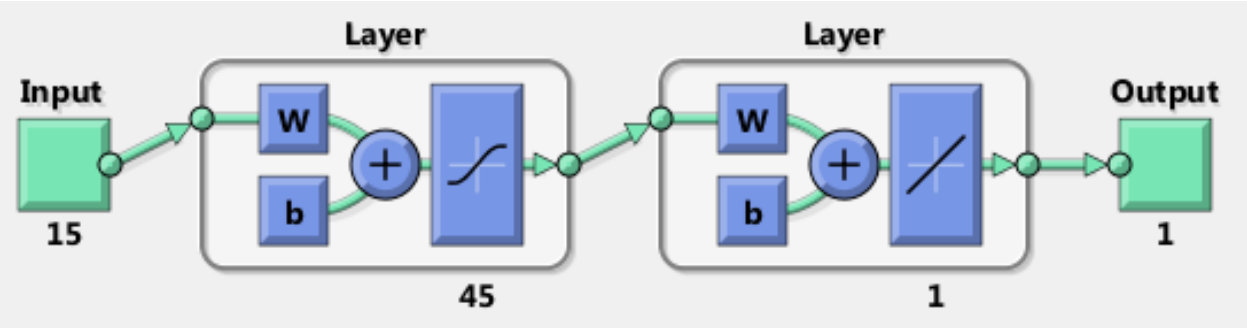

Fig. 4. Architecture of the ANN model.

The number of neurons in the hidden layer is determined by experiments (Table 1). The numerical calibration shows that 45 neurons were sufficient to reach a reasonable precision.

Table 1
Sensitivity study for the choice of hidden neurons number.

Number of neurons in the hidden layer	Number of iterations	Performance (MSE)	Correlation coefficient R
10	503	1.29×10^{-8}	0.968
15	1,034	1.20×10^{-8}	0.971
20	720	1.24×10^{-8}	0.970
25	819	1.10×10^{-8}	0.973
30	606	1.16×10^{-8}	0.972
35	623	1.14×10^{-8}	0.972
40	697	1.10×10^{-8}	0.973
45	3,289	9.01×10^{-9}	0.978
50	999	1.00×10^{-8}	0.976
60	2,904	8.98×10^{-9}	0.978
100	7,558	5.99×10^{-9}	0.985

4.2. Constitution of the ANN database

The database is split into two parts, one for training and the other for network testing. For the generation of the two databases, numerical soil models were developed using COMSOL software.

4.2.1. Training database

For the learning phase, 390 sequences of a wide frequency band random acceleration signal (White noise) are introduced as a source of excitation. Acceleration response signals will be retrieved at points on the ground at different distances from the vibrating source while varying the following parameters in order to cover a wide range of soil categories:

The Young's modulus: From 250 MPa to 1,500 MPa with a 250 MPa pitch (6 cases).

The Poisson ratio: From 0.26 to 0.46 with a 0.05 pitch (5 cases)

The density: From 1,450 kg/m^3 to 2,200 kg/m^3 with a pitch of 150 kg/m^3 (6 cases).

The distance: From 10 m to 110 m with a step of 5 m (21 cases).

A total of 1,474,200 samples constitute the database dedicated to the network training.

4.2.2. Test and validation database

To test the network, a new database which is different from the one used for training, is elaborated using parametric analyses, where the input parameters of the network were varied and shifted as follows:

The Young modulus: From 300 MPa to 1,300 MPa with a step of 200 MPa.

The Poisson ratio: From 0.27 to 0.41 with a pitch of 0.07.

The density: From 1500 kg/m^3 to 2,100 kg/m^3 with a pitch of 200 kg/m^3.

The distance: From 10 m to 90 m with a step of 10 m.

Each case is represented by a signal segment of 390 sequences, which totalize 252,720 samples employed to network testing.

4.2.3. Data Normalization

To achieve a stable solution, it is recommended that the numerical values of the input and output parameters are normalized as follows:

$$E_i^* = \frac{E_i}{\max E} \quad (1)$$

$$\rho_i^* = \frac{\rho_i}{\max \rho} \quad (2)$$

$$\upsilon_i^* = \upsilon_i \quad (3)$$

Such as:

E_i, υ_i and ρ_i: are the i-*th* values of the Young modulus, the Poisson ratio and the density respectively.

E_i*, υ_i* and ρ_i*: are the i-*th* normalized values of the Young modulus, the Poisson ratio and the density respectively.

MaxE and Maxρ: are the maximum values of the Young modulus and the density respectively.

The Poisson ratio values are between 0 and 0.5, so they are automatically normalized.

The use of a uniform unit for acceleration (g) results in a naturally normalized values between -1 and +1.

4.3. Neural networks training

For the present study for which precise learning is required, we used the Levenberg-Marquardt algorithm which has a very fast convergence. The performance function used for ANN training is Mean Square Error (MSE) [31].

4.4. Testing and validation of networks

In order to verify the proper functioning of the neural networks, all the data used for the test was passed through the network to perform a linear regression between the outputs of the Y network and the corresponding targets T (target). The validation result of the neural network for the prediction of soil accelerations at locations at different distances from the excitation source is shown in Fig. 5.

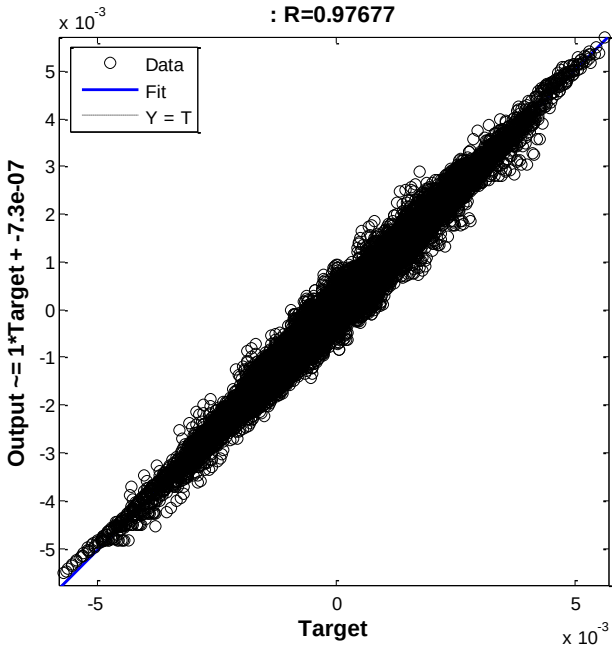

Fig. 5. Linear regression for the network test.

The correlation coefficient reached a value of R= 0.977 which is close to the unit, which means that this network gives very good predictions of the ground acceleration.

The ground acceleration signal predicted by the neural network model is plotted with the desired signal in Fig. 6. The correlation between the desired signals (EF) and those predicted by the model is ambitious. Moreover, ground acceleration peaks are predicted with an error of 1.42 %.

The relative error ε on the prediction of acceleration peaks is calculated according to:

$$\varepsilon = \frac{|A_{FE} - A_{NN}|}{|A_{FE}|} \tag{4}$$

Such as:

ε: Relative error between the acceleration peak given by the ANN and the acceleration peak given by FE;

A_{NN}: The peak of ground acceleration predicted by the ANN model;

A_{FE}: The peak of ground acceleration computed by the FE model.

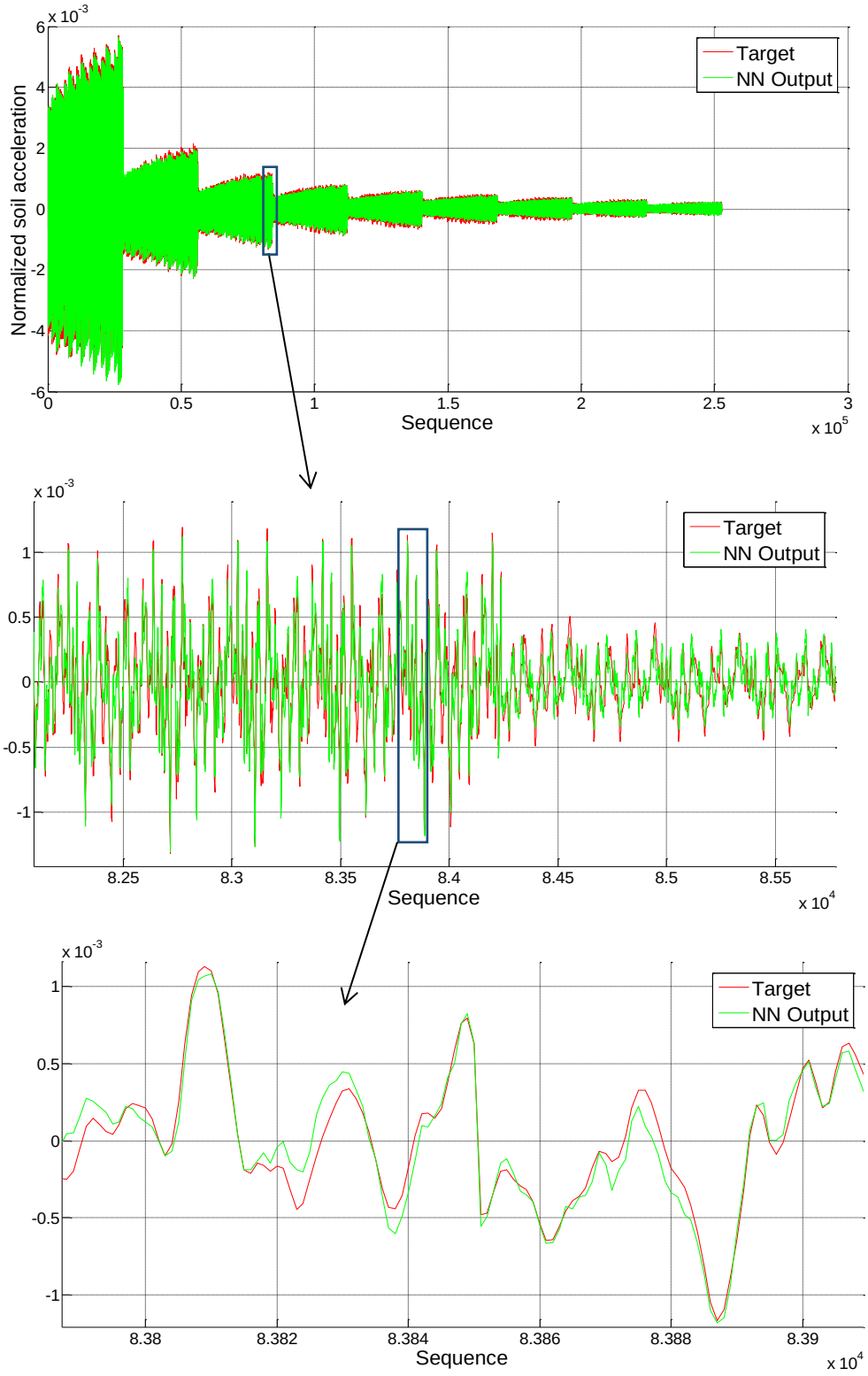

Fig. 6. Target and predicted signals.

5. Vibration Prediction of heterogeneous soil

An example of heterogeneous soil is proposed to test the ability of the generalized network to predict the accelerations of a stratified soil. The characteristics of each layer of heterogeneous soil are presented in Table 2.

Table 2
Geotechnical characteristics of the soil example.

Layers	Depth (m)	Elasticity module E (MPA)	Specific mass ρ (Kg/m^3)	Poisson ratio ν
1	0 -1.5	600	1,700	0.30
2	1.5 - 2.5	1,200	1,750	0.32
3	2.5 – 5.0	2,000	1,600	0.35
4	5.0 - 6.5	4,000	1,800	0.25
5	6.5 - 9.0	3,000	1,650	0.30

Before predicting, by the ANN model, the dynamic response of the stratified soil, it is necessary to go through the homogenization of the soil and obtain the mechanical properties of a single-layer soil equivalent to the stratified soil.

The homogenized mechanical properties are determined using the simplified approach described by Berthelot [36]:

Elasticity module E:

Using the following formula:

$$E = E_1 f_1 + E_2 f_2 + E_3 f_3 + E_4 f_4 + E_5 f_5 \quad (5)$$

With: $E_1$to E_5 are Elasticity modules and $f_1$to f_5, the volumetric fractions of the layers 1 to 5 respectively.

The volume fraction of layer n is calculated by:

$$f_n = \frac{V_n}{V_t} \quad (6)$$

Where:

V_n: The volume of layer n

V_t: Total volume of soil ($V_t = V_1 + V_2 + V_3 + V_4 + V_5$)

We obtain: E = 2,288.89 MPa

Poisson ratio υ:

Using the formula:

$$\upsilon = \upsilon_1 f_1 + \upsilon_2 f_2 + \upsilon_3 f_3 + \upsilon_4 f_4 + \upsilon_5 f_5 \quad (7)$$

With: $\upsilon_1$to υ_5 are the Poisson ratios of the layers 1 to 5 respectively.

We obtain: $\upsilon = 0.3078$

Specific mass ρ:

Using the following formula:

$$\rho = \rho_1 f_1 + \rho_2 f_2 + \rho_3 f_3 + \rho_4 f_4 + \rho_5 f_5 \quad (8)$$

With: $\rho_1$to ρ_5 are specific mass of the layers 1 to 5 respectively.

We obtain: ρ = 1,681 kg/m^3.

The soil properties (E = 2,288.89 MPa, υ = 0.3078 and ρ = 1,681 kg/m^3) as well as the source signal (acceleration signal generated according to the following earthquake ground motions collected during the Boumerdes' earthquake in Algeria, 21 May 2003 at the station of Keddara) and the distances between the measuring points and the source are presented at the input of the neural network to predict the dynamic responses of the soil.

The responses predicted by the network will be compared with the desired ones given by the numerical model FE.

The linear regression curve of the neural network for the accelerations prediction of the stratified soil at 9 different location distances from the source of vibration is shown in Fig. 7.

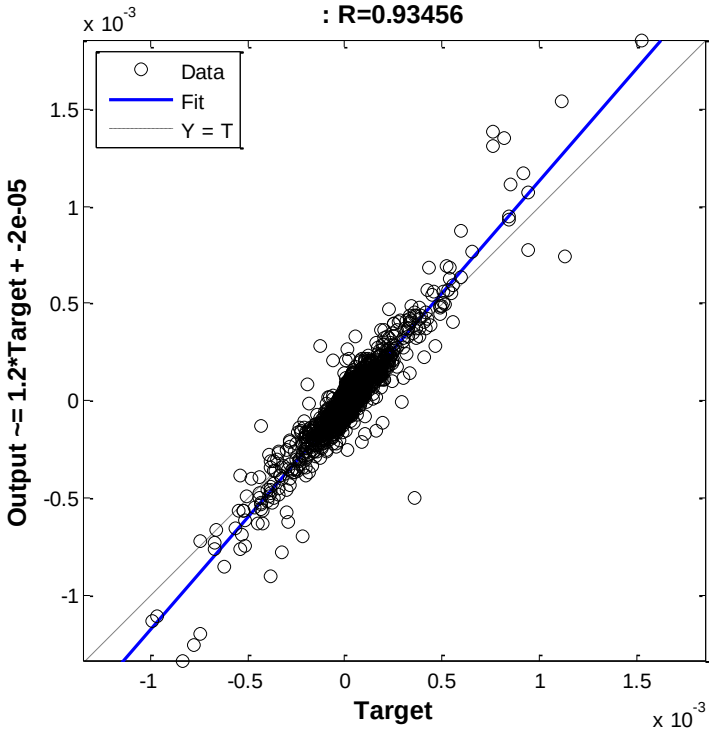

Fig. 7. Linear regression of the stratified soil response signal for the generalized model.

The stratified soil acceleration signal predicted by the generalized neural network model is plotted with the desired signal in Fig. 8.

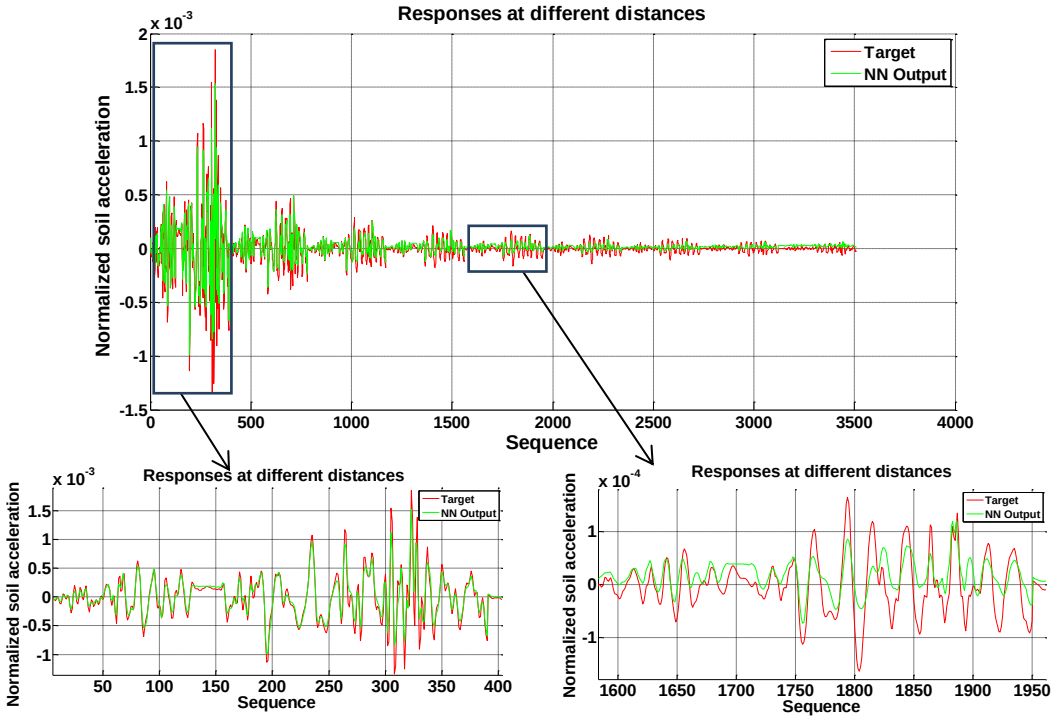

Fig. 8. The generalized network output signal and the desired stratified soil response signal.

As shown in Fig. 8, the desired signals (FE) and those predicted by the ANN generalized model are in good agreement where the linear regression factor reaches 93%, especially in the near field, although the phenomenon is very complicated, namely the heterogeneity and diversity of soils.

6. Discussion

In our research, we based ourselves on the acceleration of the ground at the level of the source regardless of the origin of vibration.

Each source of vibration is characterized by its amplitude and its frequency. We varied the two parameters at the same time by a random signal in white noise, to cover all sources of vibration.

In this work, we have two kinds of results; the first ones concern homogeneous soil and the second cover stratified soil response, such that the prediction of the accelerations of homogeneous soils is almost perfect in terms of signal (R=98%) or acceleration peak (error=1.42%). On the other hand the proposed ANN model gives good results for the prediction of the temporal response of heterogeneous soils (R=93%) with an error that reaches 17% for the prediction of acceleration peaks.

The network works flawlessly on the near field. Although on the far field especially for the heterogeneous ground, the model presents certain limitations. This can be seen in Fig. 8, in

which sequences less than 400 correspond to measurement points located at distances close to the source of vibration unlike sequences greater than 1600 which correspond to measurement points located at distances far from the source of vibration. The ground acceleration values over long distances from the source are about 10% of those over short distances. Consequently, predicting small acceleration values becomes more challenging, particularly when they approach zero.

For this reason, it is recommended to make improvements on the network to fill this gap or on the way of homogenizing stratified soil.

7. Conclusion

This paper proposes a generalized neural network model capable to predict the time history responses of any type of soil at a distant point from any vibrating source. Large number of samples, covering all possible combinations of discretized soil properties within their relative variation ranges, has been automatically generated using finite element software. The training dataset is constituted of all the generated samples including realistic and non-realistic soil properties. This helps to cover heterogeneous soils with homogenized equivalent properties obtained as a linear combination of realistic properties. A second dataset is generated using shifted soil properties samples to test the network. Very good results have been obtained where the correlation between the desired ground acceleration signals predicted by the generalized ANN model expressed by the linear regression coefficient R reached 98 % and the error in predicting the PGA is less than 2%.

A demonstrating case to predict the time history on a heterogeneous soil at different distances from the vibrating source confirms the test performance of the proposed ANN model although the complexity of the situation with regard to soil heterogeneity and diversity. Regarding the limitless of the sampling resolution combined to the homogenization technique, the ANN model can be generalized to a wide range of practical applications. Where the signals predicted by this network can be used to verify the stability of adjacent constructions under the effect of dynamic excitation at the source. The only weakness is that the distance is still low where the model has been tested with distances less than 110m, i.e. in the close vicinity to the vibration source.

The proposed model can be used in the case of soils which present a horizontal heterogeneity (in plan), this by the recurrent use of the ANN model in such a way that the output of the model (acceleration of the soil at the last point of the first soil) will be used as input of the network for the second ground (source acceleration signal), and so on.

Our ANN model is able to determine the ground vibrations at different distances from a vibration source. It can be used for several applications. For example, this model can be used to assess and predict ambiguous ground vibrations due to blasting, at certain distances from the blast front, with the aim of monitoring and predicting ambiguous vibration levels and taking measures to reduce their dangerous effect. We can also use the proposed ANN model to assess the level of vibration at a certain distance near the railway tracks. It can be integrated into the real-time vibration control systems of rail transport systems in urban areas, in order to minimize the

consequent environmental impacts. A similar protocol can be developed for an earthquake early warning system, where the magnitude and extent of vibrations due to earthquakes can be assessed by the proposed ANN using the signal recorded by the sensor as input to the network.

According to the results obtained, the grating works perfectly in the near field in terms of signal and peak acceleration. However, it relatively loses accuracy in the far field especially for heterogeneous soils. For this reason, improvements to the proposed method in the far field are recommended. Within the context of the present research work, an ongoing research program includes an experimental verification of the model and an extension of the approach for earthquake ground motion prediction.

Funding

This research received no external funding.

Conflicts of interest

The authors declare no conflict of interest.

Authors contribution statement

Ismail Derbal, Nouredine Bourahla: Conceptualization; Ismail Derbal: Data curation; Ismail Derbal, Ahmed Mebarki: Formal analysis; Ismail Derbal: Investigation; Ismail Derbal, Nouredine Bourahla, Ahmed Mebarki: Methodology; Ismail Derbal: Project administration; Ismail Derbal: Resources; Ismail Derbal: Software; Ismail Derbal, Ahmed Mebarki: Supervision; Nouredine Bourahla, Ahmed Mebarki, Ramdane Bahar: Validation; Ismail Derbal: Visualization; Ismail Derbal: Roles/Writing – original draft; Nouredine Bourahla, Ahmed Mebarki, Ramdane Bahar: Writing – review & editing.

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